

# Artificial Intelligence: The Next Paradigm Shift in Medical Education

*Cornelius A. James, MD*  
*Erkin Ötleş, MS*

9/14/2023

# Objectives

- Define artificial intelligence (AI) and machine learning (ML)
- Describe the impact that AI/ML will have on health care
- Summarize the current state of AI/ML in medical education
- Provide a vision for AI/ML in medical education
- **Provoke thought and dialogue**



# Potential Conflicts of Interest

Dr. James: none applicable

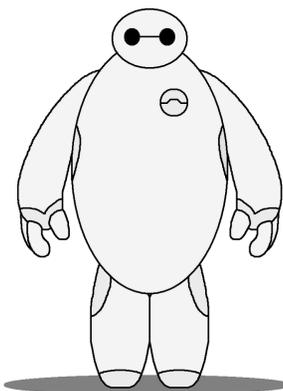
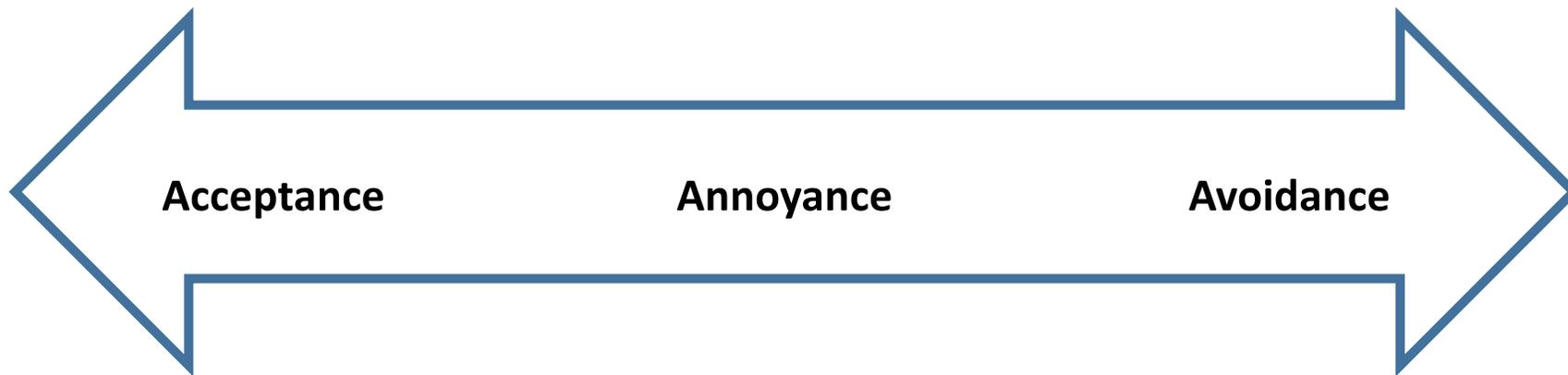
Erkin: none directly related to today's talk

Patent pending: AI prediction of health outcomes in patients with occupational injuries.

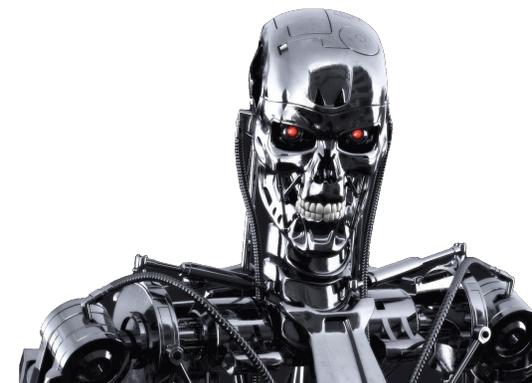
Small amount of IRA stock in various technology & healthcare companies.

Provide AI advising for several companies.

**What comes to mind when you think about AI?**



Hello! I am Baymax, your personal healthcare companion.



# What is AI?

# What is AI?

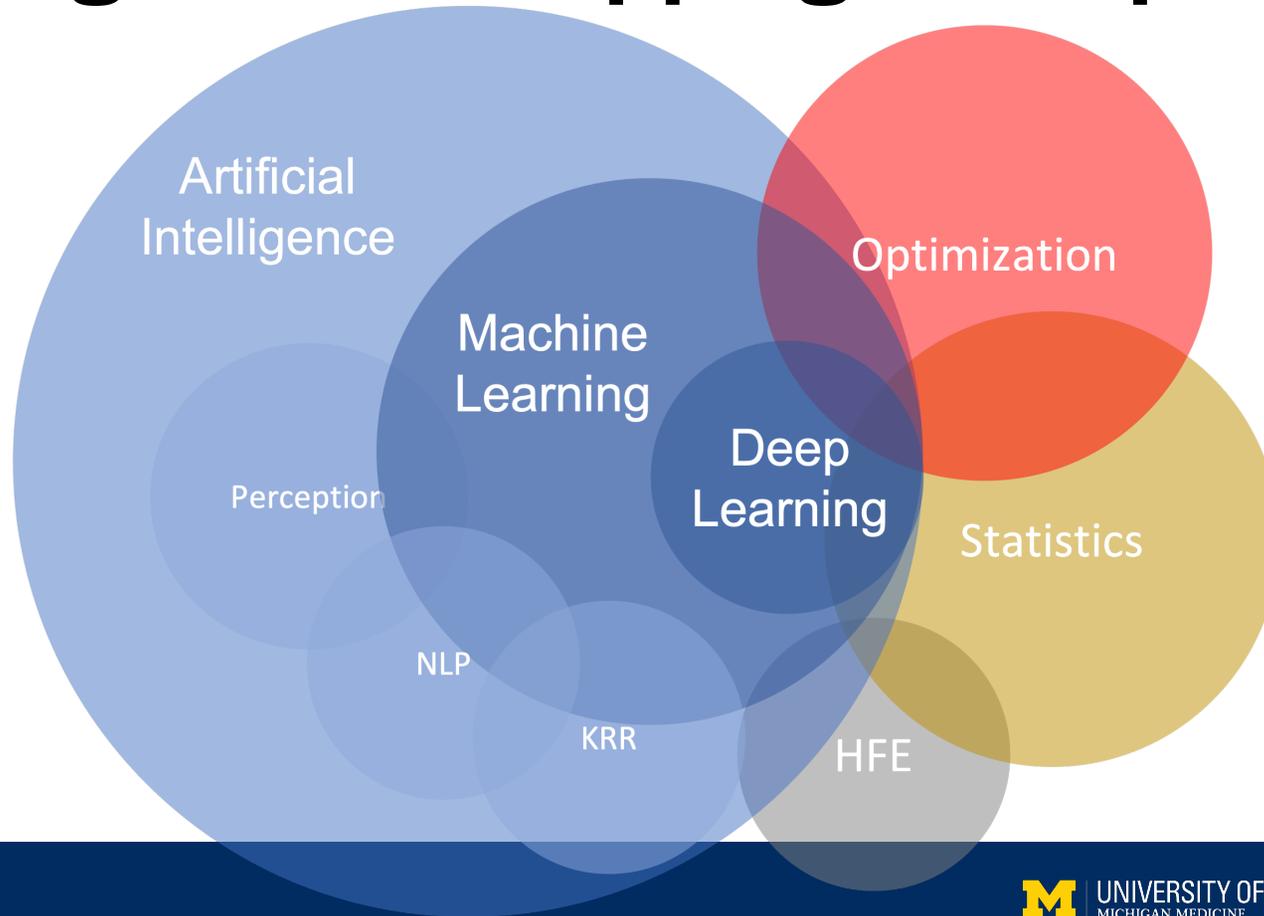
*It is not magic.*

# First, some definitions

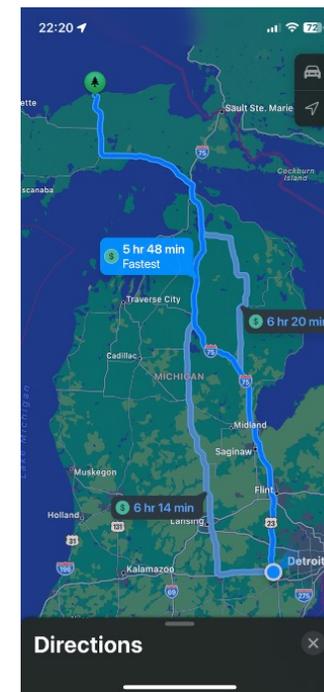
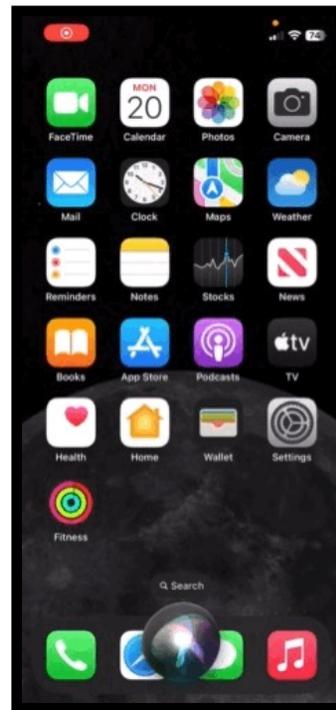
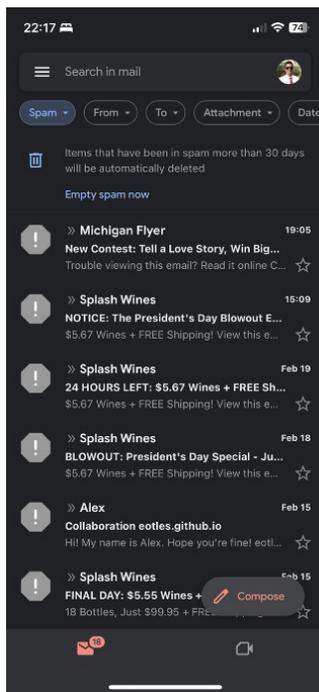
**Artificial Intelligence (AI):** *intelligence* (perceiving, synthesizing, and inferring information) demonstrated by machines

**Machine Learning (ML):** field of inquiry devoted to understanding and building methods that *learn* (use data to improve performance on a task).

# Nesting and overlapping concepts



# AI is ubiquitous in everyday life



# Many industries depend on AI

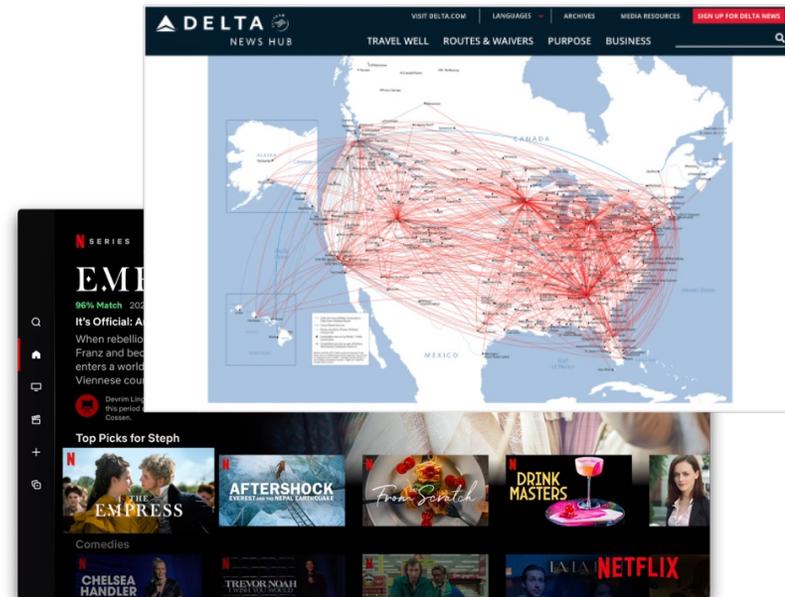
What routes should we fly?

When should we service our planes?

How should we price a product?

What content should we serve?

What products should we stock?



# How does ChatGPT work?

# ChatGPT = Chatbot + GPT3

Chatbot: developed by OpenAI  
mix of supervised & reinforcement learning

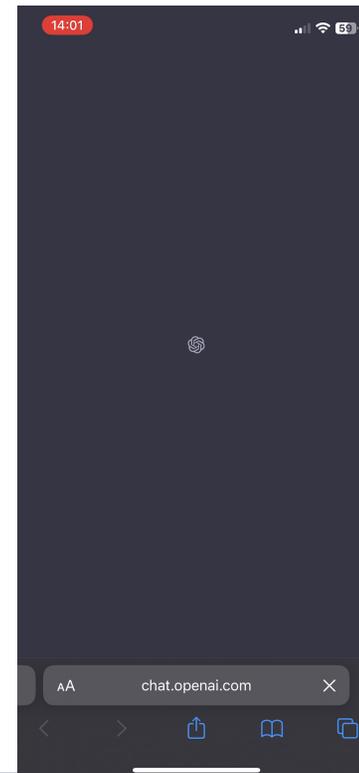
GPT3: Generative Pre-trained Transformer 3  
type of **large language model** (fancy predictive text)

“The quick brown fox jumps over the \_\_\_\_\_”

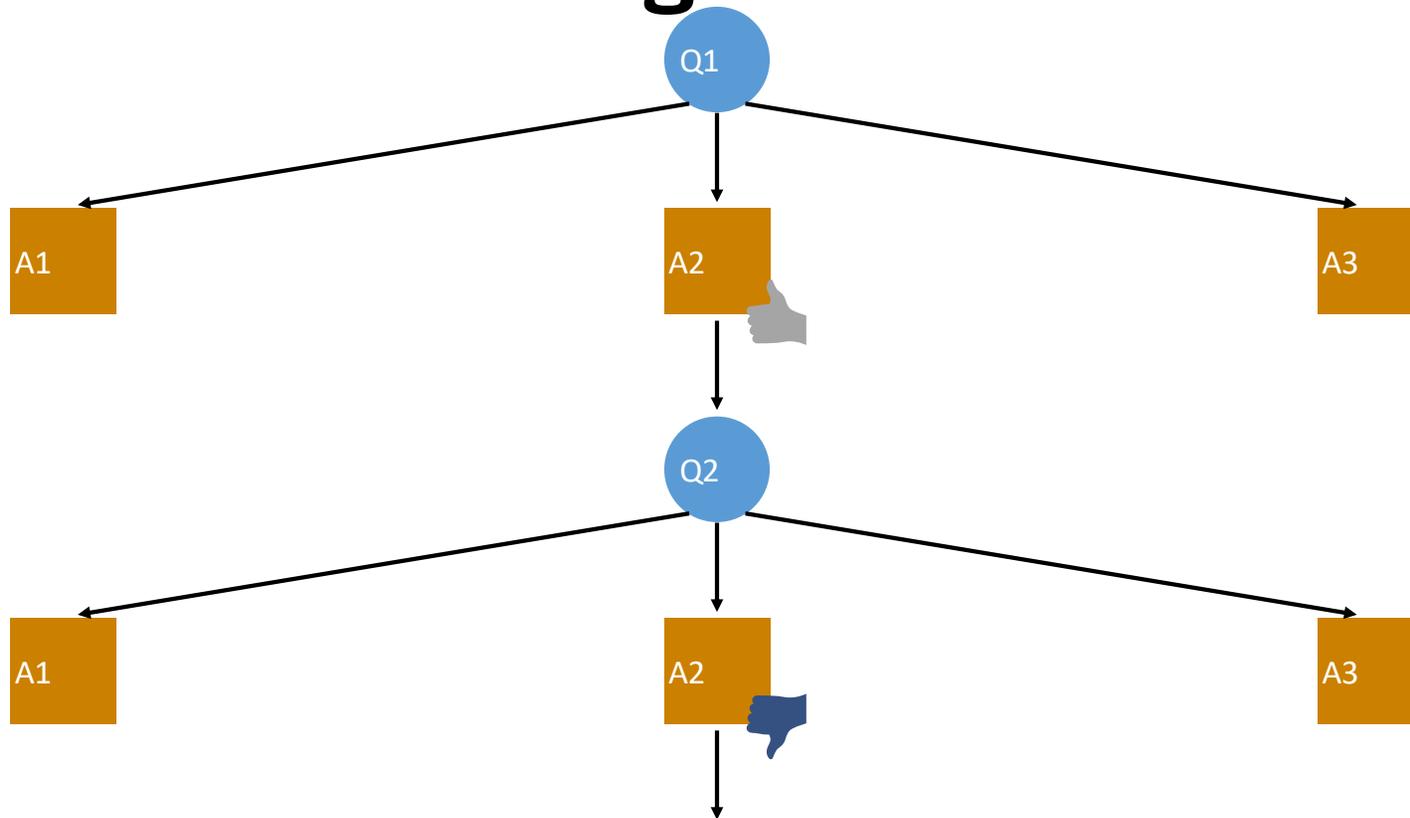
Lazy 95%  
Slow 2%  
Fun 1%

Žyzzzyva 0%

Trained on all available text on the internet



# Chat is a branching tree



# Major issues with large language models

Based on what ever data it was trained on

- May not be relevant, accurate, or pleasant

Generative process is inherently stochastic

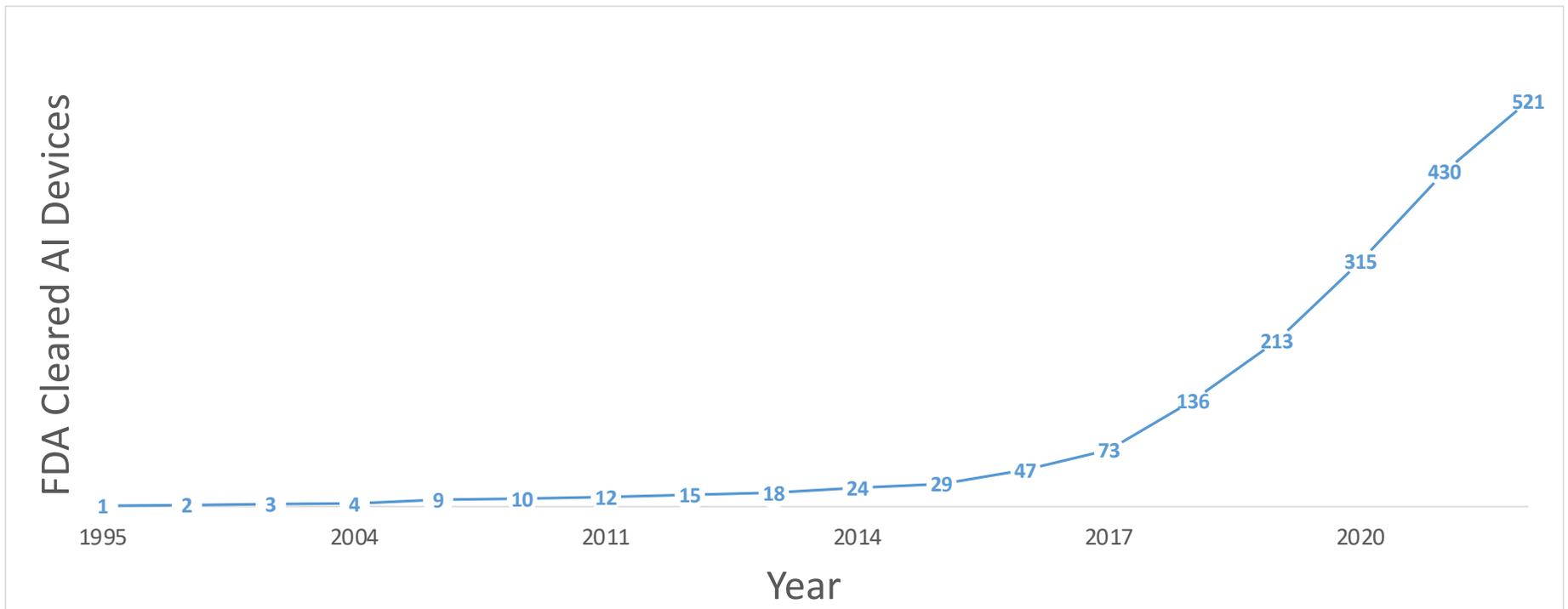
- Response choices and sentence construction depend on sampling distributions randomly

Hard to evaluate and verify

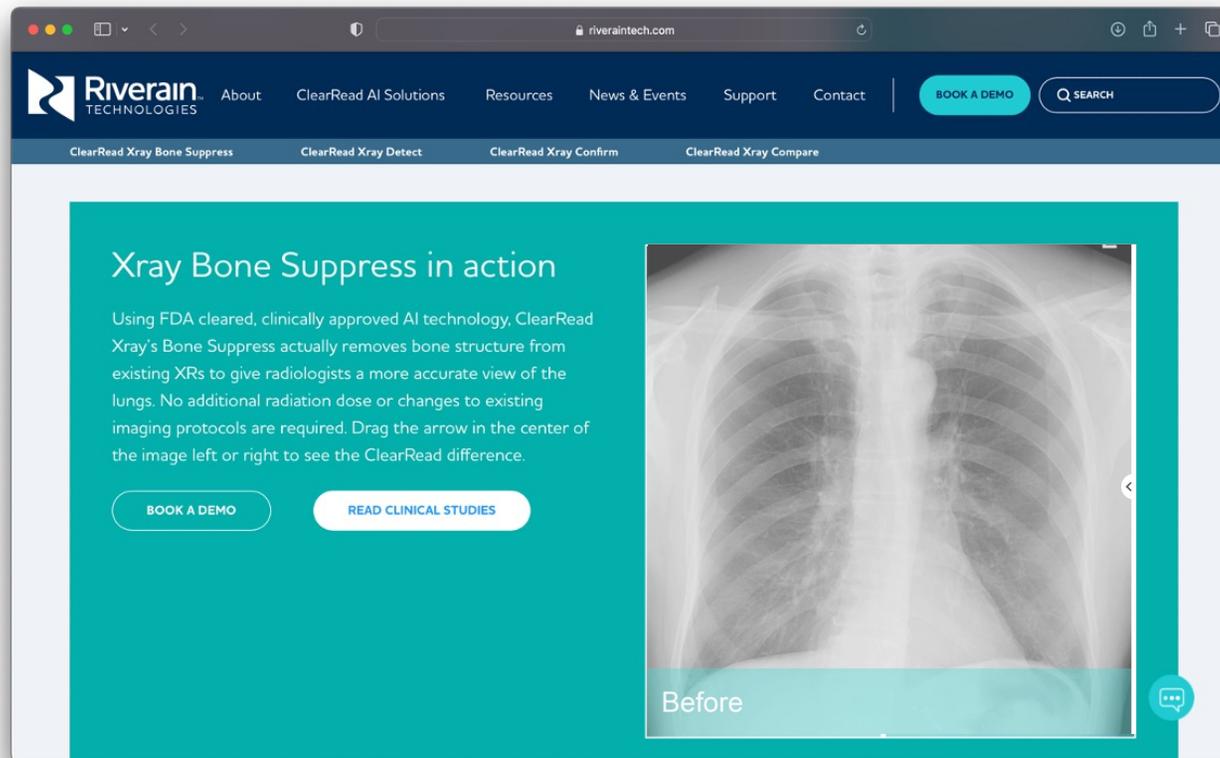
- How often will it be right? What is right?

# How is AI used in healthcare?

# Increasing prevalence of medical AI



# AI in use at Michigan Medicine



# Other examples of AI in use

Add evaluation NLP

**THE JOURNAL OF UROLOGY**

**Development and Validation of Models to Predict Pathological Outcomes of Radical Prostatectomy in Regional and National Cohorts**

Erin Oley<sup>1</sup>, Brian T. Denton<sup>1,2</sup>, Bo Gu<sup>1,3</sup>, Adnan Murat<sup>1,4</sup>, Seim Menden<sup>1</sup>, Gregory B. Auffenberg<sup>1</sup>, Spencer C. Miller<sup>1</sup>, Brian R. Lane<sup>1</sup>, Anish K. George<sup>1</sup> and Karandeep Singh<sup>1,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32,33,34,35,36,37,38,39,40,41,42,43,44,45,46,47,48,49,50,51,52,53,54,55,56,57,58,59,60,61,62,63,64,65,66,67,68,69,70,71,72,73,74,75,76,77,78,79,80,81,82,83,84,85,86,87,88,89,90,91,92,93,94,95,96,97,98,99,100</sup> for the Michigan Urological Surgery Improvement Collaborative

**Purpose:** Prostate cancer is recommended by national guidelines to support clinical decisions leading to prostate cancer. Existing models to predict pathological outcomes of radical prostatectomy (RP)—the Memorial Sloan-Kettering (MSK) model, Partin table, and the Briganti nomogram—have been developed using data from tertiary care centers and may not generalize well to other settings.

**Materials and Methods:** Data from a regional cohort (Michigan Urological Surgery Improvement Collaborative [MUSIC]) were used to develop models to predict pathological outcomes (EPS), seminal vesicle invasion (SVI), lymph node invasion (LNI), and nonorgan-confined disease (NOCD), in patients undergoing RP. The MUSIC model was compared against the MSK model, Partin table, and Briganti nomogram (all using data from a national cohort [International Epidemiology and End Results [IIEER] registry]).

**Results:** We identified 7,611 eligible patients in the IIEER register. The MUSIC model had good discrimination (AUC: EPS: 0.77, SVI: 0.81, LNI: 0.80, NOCD: 0.77) and was well calibrated. While the MSK model had similar discrimination to the MUSIC model (AUC: EPS: 0.74, SVI: 0.81, LNI: 0.81, NOCD: 0.76), they overestimated the risk of EPS, LNI, and NOCD. The Partin table had inferior discrimination (AUC: EPS: 0.67, SVI: 0.76, LNI: 0.76, NOCD: 0.74).

**Conclusion:** The MUSIC model had good discrimination and was well calibrated. The MSK model had similar discrimination to the MUSIC model but overestimated the risk of EPS, LNI, and NOCD. The Partin table had inferior discrimination (AUC: EPS: 0.67, SVI: 0.76, LNI: 0.76, NOCD: 0.74).

Prostate Cancer Outcomes

Proceedings of Machine Learning Research (PMLR) 2021

**Mind the Performance Gap: Examining Dataset Shift During Prospective Validation**

From Oley<sup>1,2</sup>

**HHS Public Access**

**A Generalizable, Data-Driven Approach to Predict Daily Risk of Clostridium difficile Infection at Two Large Academic Health Centers**

Joanna Oh, MS<sup>1,2</sup>, Megan Mahan, MS<sup>1,3</sup>, Christopher Frazee, BS<sup>1</sup>, Robert McCarthy, BS<sup>1</sup>, Kristina Das, MD, MS<sup>1,4</sup>, Sara C. Ryan, MD, PhD<sup>1,5</sup>, Lauren Whelan, MD<sup>1,6</sup>, Lauren R. Weid, MPH<sup>1,7</sup>, Vincent B. Young, MD, PhD<sup>1,8</sup>, John Guttag, PhD<sup>1,9</sup>, David C. Hooper, MD<sup>1,10</sup>, Eric S. Denney, MD, PhD<sup>1,11,12</sup>, and James Wang, PhD<sup>1,13</sup>

**Objective:** To develop a generalizable, data-driven approach to predict daily risk of Clostridium difficile infection (CDI) at two large academic health centers.

**Methods:** We used data from two large academic health centers to develop a generalizable, data-driven approach to predict daily risk of CDI. We used a machine learning approach to predict daily risk of CDI. We used a machine learning approach to predict daily risk of CDI. We used a machine learning approach to predict daily risk of CDI.

**Results:** We developed a generalizable, data-driven approach to predict daily risk of CDI. We used a machine learning approach to predict daily risk of CDI. We used a machine learning approach to predict daily risk of CDI.

**Conclusion:** We developed a generalizable, data-driven approach to predict daily risk of CDI. We used a machine learning approach to predict daily risk of CDI. We used a machine learning approach to predict daily risk of CDI.

In Hospital Infection Risk

**RESEARCH, SPECIAL PAPERS**

**Early Identification of patients admitted to hospital for covid-19 at risk of clinical deterioration: model development and multistate external validation study**

Fahad Karim<sup>1</sup>, Sheeraz Tahir<sup>1</sup>, Erik Olesen<sup>1,2</sup>, David Smith<sup>1,3</sup>, Sarah S. Valleron<sup>1,4</sup>, Ben Gong<sup>1</sup>, Benjamin D. L. Ryan<sup>1,5</sup>, James D. Hens<sup>1,6</sup>, and Robert H. Hens<sup>1,7</sup>

**Objective:** To develop a model to identify patients at risk of clinical deterioration during their hospital stay.

**Methods:** We used data from a large hospital to develop a model to identify patients at risk of clinical deterioration. We used a machine learning approach to predict clinical deterioration. We used a machine learning approach to predict clinical deterioration.

**Results:** We developed a model to identify patients at risk of clinical deterioration. We used a machine learning approach to predict clinical deterioration. We used a machine learning approach to predict clinical deterioration.

**Conclusion:** We developed a model to identify patients at risk of clinical deterioration. We used a machine learning approach to predict clinical deterioration. We used a machine learning approach to predict clinical deterioration.

Deterioration Risk

**JAMA Internal Medicine | Original Investigation**

**External Validation of a Widely Implemented Proprietary Sepsis Prediction Model in Hospitalized Patients**

Andrew H. Lee, MD, PhD<sup>1,2</sup>, Daniel J. Tancredi, MD, PhD<sup>1,3</sup>, and James M. T. Spang, MD, PhD<sup>1,4</sup>

**Objective:** To evaluate the performance of a widely implemented proprietary sepsis prediction model in a large, diverse population of hospitalized patients.

**Methods:** We used data from a large hospital to evaluate the performance of a widely implemented proprietary sepsis prediction model. We used a machine learning approach to predict sepsis. We used a machine learning approach to predict sepsis.

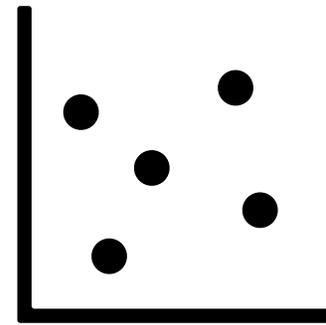
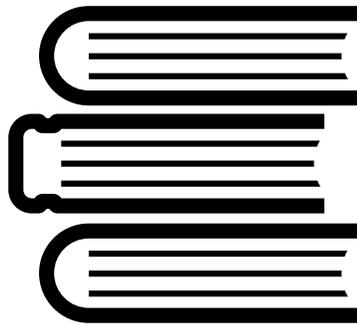
**Results:** We evaluated the performance of a widely implemented proprietary sepsis prediction model. We used a machine learning approach to predict sepsis. We used a machine learning approach to predict sepsis.

**Conclusion:** We evaluated the performance of a widely implemented proprietary sepsis prediction model. We used a machine learning approach to predict sepsis. We used a machine learning approach to predict sepsis.

In Hospital Sepsis Risk

# Why should we train physicians on AI?

# AI has the potential to advance medicine



AI has techniques to rapidly **summarize** information, **predict** outcomes, and **learn** over time

Society has big expectations for AI in medicine

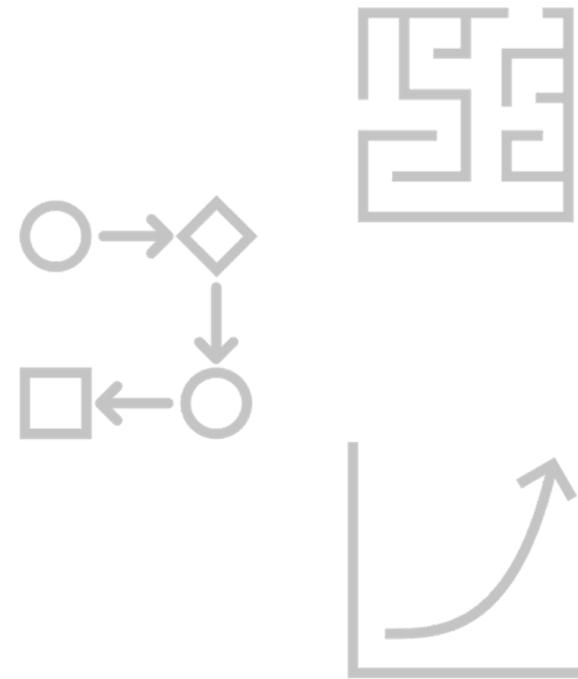
# AI is not a part of medical education

Use of AI in medicine is not straightforward

AI tools depend on complicated data and workflows that physicians understand

Medical AI adoption increasing

**Learners unprepared to use, assess, and develop AI tools**



# We've got to start training physicians on AI fundamentals

Physicians shouldn't just be "users"

Should be actively involved in creating, evaluating, and improving AI

Leadership in AI dependent on:  
**understanding** how it works &  
**partnership** with engineers

Cell Reports Medicine

CellPress  
OPEN ACCESS

Commentary  
**Teaching artificial intelligence as a fundamental toolset of medicine**

Erkin Ötleş,<sup>1,2,3,4,5,6,7</sup> Cornelius A. James,<sup>2,3</sup> Kimberly D. Lomis,<sup>1</sup> and James O. Woolliscroft<sup>8</sup>

<sup>1</sup>Medical Scientist Training Program, University of Michigan Medical School, Ann Arbor, MI, USA  
<sup>2</sup>Department of Industrial and Operations Engineering, University of Michigan, Ann Arbor, MI, USA  
<sup>3</sup>Department of Pediatrics, University of Michigan, Ann Arbor, MI, USA  
<sup>4</sup>American Medical Association, Chicago, IL, USA  
<sup>5</sup>Departments of Internal Medicine and Learning Health Sciences, University of Michigan, Ann Arbor, MI, USA  
<sup>6</sup>Present address: 1225 Beal Avenue, Ann Arbor, MI 48109, USA  
<sup>7</sup>Twitter: @erkin  
<sup>8</sup>Correspondence: [woollisc@umich.edu](mailto:woollisc@umich.edu)  
<https://doi.org/10.1016/j.crm.2022.100824>

Artificial intelligence (AI) is transforming the practice of medicine. Systems assessing chest radiographs, pathology slides, and early warning systems embedded in electronic health records (EHRs) are becoming ubiquitous in medical practices. Despite this, medical students have minimal exposure to the concepts necessary to utilize and evaluate AI systems, leaving them under prepared for future clinical practice. We must work quickly to bolster undergraduate medical education around AI to remedy this. In this commentary, we propose that medical educators treat AI as a critical component of medical practice that is introduced early and integrated with the other core components of medical school curricula. Equipping graduating medical students with this knowledge will ensure they have the skills to solve challenges arising at the confluence of AI and medicine.

The promise of artificial intelligence (AI) to aid the practice of medicine has long been a topic of discussion.<sup>1</sup> What was once an abstract discussion of the future of medicine is now a clinical reality. Software employing AI is found throughout the clinical care continuum. The US Food and Drug Administration (FDA) has approved over 100 AI software devices.<sup>2</sup> The purposes of these software devices range from measuring pulmonary nodules in chest CT scans to detecting different cell types in peripheral blood smears and screening for diabetic retinopathy using photos taken in primary-care settings. However, not all AI systems require FDA approval. Some of the most widely deployed AI systems are early warning systems that fall outside the FDA's jurisdiction. AI systems for detecting in-hospital deterioration and sepsis are deployed at hundreds of US hospitals.<sup>3</sup> The recent increased interest in medical AI is due to the availability of massive amounts of data, facilitated by widespread adoption of electronic health records (EHRs), and advances in AI techniques, driven by a combination of new hardware and computational methods.

Despite the accelerating use of AI in clinical practice, the pace of incorporating AI concepts into medical education has been slow and superficial.<sup>4</sup> Only recently has it been proposed that AI concepts be included in medical education curricula.<sup>5,6</sup> Most suggestions to date have framed training in AI as an added layer to current medical school curricula, hereafter referred to as undergraduate medical education (UME). Recommendations for incorporating AI into UME range widely, covering the gamut from teaching medical students how to code to EHR usage and the ethics surrounding the adoption of AI.<sup>7</sup> However, proposals that treat AI as an additional curricular element or course struggle to gain traction in an over-crowded curriculum. In this commentary, we offer the collective perspective of a medical student, practicing physician, and medical educators. We propose that medical schools view AI as a fundamental component of medical practice and deeply integrate it throughout UME.<sup>8</sup>

We believe UME must quickly transition to address AI as a fundamental toolset, meaning that it contains many interrelated techniques that underpin the practice of medicine across specialties and care environments. However, the breadth of AI presents a challenge for medical educators seeking to provide a foundation in UME that can be built upon throughout one's career. AI uses computational methods to process data, from identifying a pattern to generating a prediction or a recommendation. AI can be considered an umbrella term encapsulating many techniques, such as natural language processing and machine learning (ML). Practices from computer science, statistics, decision science, and operations research intersect with AI. These procedures are built upon a foundation of data processing dependent on two types of thinking: computational—being able to provide instructions to computers unambiguously—and statistical—being able to analyze the information derived from processes subject to randomness.

To add to the challenge, like the practice of medicine, the practice of AI is a combination of art and science, as AI systems are components of even larger and more complicated socio-technical systems. Therefore, in addition to technical knowledge, applying AI effectively in clinical practice demands careful consideration of the context, patient values and preferences, ethics, policy, and physician user experiences.

Cell Reports Medicine 3, 100824, December 20, 2022 © 2022 The Author(s). 1  
This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

**Are you currently using AI for teaching (instruction, assessment)?**



**Are you currently teaching about the role of AI in health care?**





VIEWPOINT

## Artificial Intelligence in Health Care A Report From the National Academy of Medicine

- Promote population-representative data with accessibility, standardization and quality is imperative.
- Prioritize ethical, equitable and inclusive medical AI while addressing explicit and implicit bias.
- Contextualize the dialogue of transparency and trust, which means accepting differential needs.
- Focus in the near term on augmented intelligence rather than autonomous agents.
- **Develop and deploy appropriate training and educational programs.**
- Leverage frameworks and best practices for learning health care systems, human factors and implementation science.
- Balance innovation with safety through regulation and legislation to promote trust.

DISCUSSION PAPER

### Artificial Intelligence for Health Professions Educators

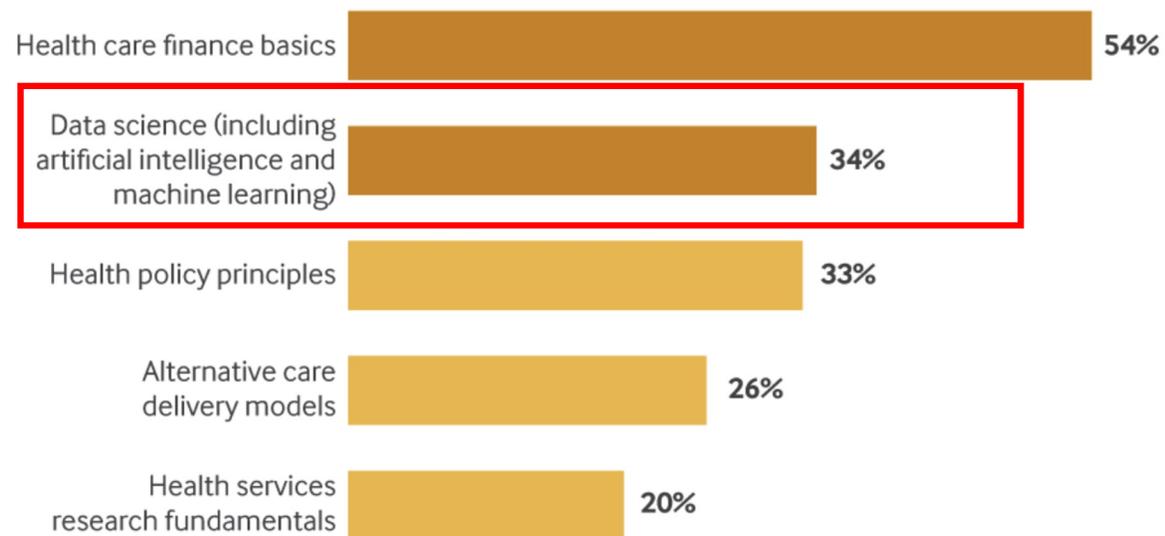
**Kimberly Lomis, MD**, American Medical Association; **Pamela Jeffries, PHD, RN, FAAN, ANEF**, Vanderbilt School of Nursing; **Anthony Palatta, DDS, EdD**, PalattaSolutions; **Melanie Sage, PHD, MSW**, University at Buffalo School of Social Work; **Javaid Sheikh, MD, MBA**, Weill Cornell Medicine-Qatar; **Carl Sheperis, PhD, MS**, Texas A&M University-San Antonio; and **Alison Whelan, MD**, Association of American Medical Colleges

September 8, 2021

James CA, Wachter RM, Woolliscroft JO. Preparing Clinicians for a Clinical World Influenced by Artificial Intelligence. *JAMA*. 2022;327(14):1333-1334.

# NEJM Poll

What are the top two topics that medical schools should focus on to prepare students to succeed?



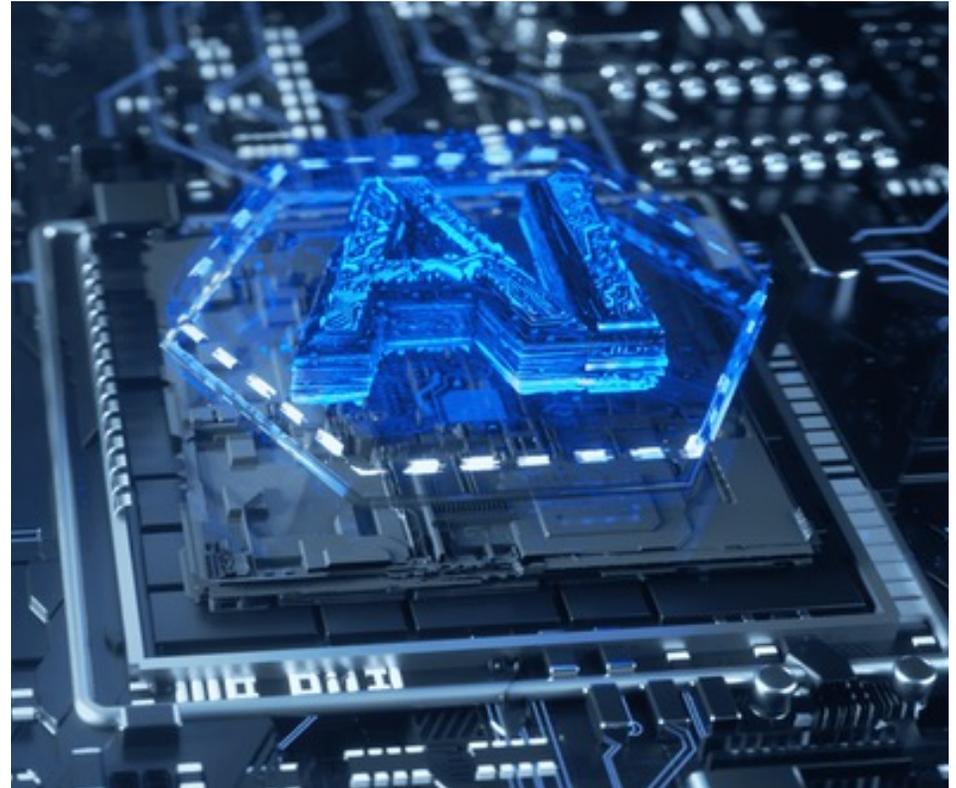
Base: 801 (multiple responses)

NEJM Catalyst ([catalyst.nejm.org](http://catalyst.nejm.org)) © Massachusetts Medical Society

Mohta N, Johnston SC. Medical education in need of a 2020 revamp. *NEJM Catalyst*. 2020;1(3):1-7.

# Current State

- Electives
- Online courses, modules
- Workshops
- Certificate programs
- Interest groups



1. Paranjape K, Schinkel M, Nannan Panday R, Car J, Nanayakkara P. Introducing Artificial Intelligence Training in Medical Education. *JMIR Med Educ.* 2019;5(2):e16048.
2. Lee J, Wu AS, Li D, Kulasegaram KM. Artificial Intelligence in Undergraduate Medical Education: A Scoping Review. *Acad Med.* 2021;96(11S):S62-S70.

# Goals of AI/ML Instruction

- Data-savvy consumers
- Patient advocacy
- Fundamental concepts
- Appraisal, evaluation
- Clinical application
- Biases, legal, ethical considerations
  - Clinical and systems level
- Data stewardship and data quality assurance



Shift focus from “information acquisition” to “information management”

# Competencies for the Use of Artificial Intelligence–Based Tools by Health Care Professionals

Regina G. Russell, PhD, MA, MEd, Laurie Lovett Novak, PhD, Mehool Patel, MD, Kim V. Garvey, PhD, MS, MLIS, Kelly Jean Thomas Craig, PhD, Gretchen P. Jackson, MD, PhD, Don Moore, PhD, and Bonnie M. Miller, MD, MMHC

JMIR MEDICAL EDUCATION

Weidener & Fischer

[Original Paper](#)

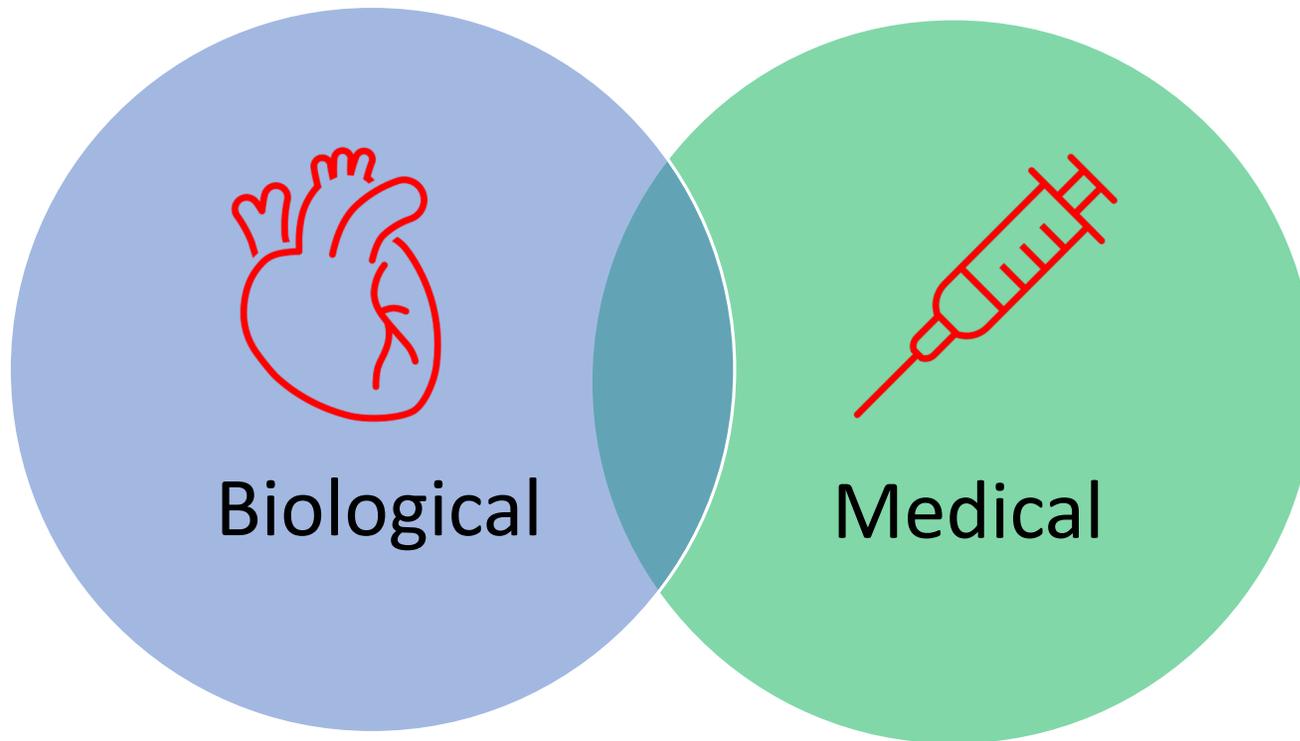
## Artificial Intelligence Teaching as Part of Medical Education: Qualitative Analysis of Expert Interviews

AI-Related Clinical Competencies for Health Care Professionals				
Basic Knowledge of AI	Social and Ethical Implications of AI	Workflow Analysis for AI-Based Tools	AI-Enhanced Clinical Encounters	Evidence-Based Evaluation of AI-Based Tools
Practice-Based Learning and Improvement Regarding AI-Based Tools				

**Table 1.** Overview of the 3 defined main categories with the associated 9 subcategories.

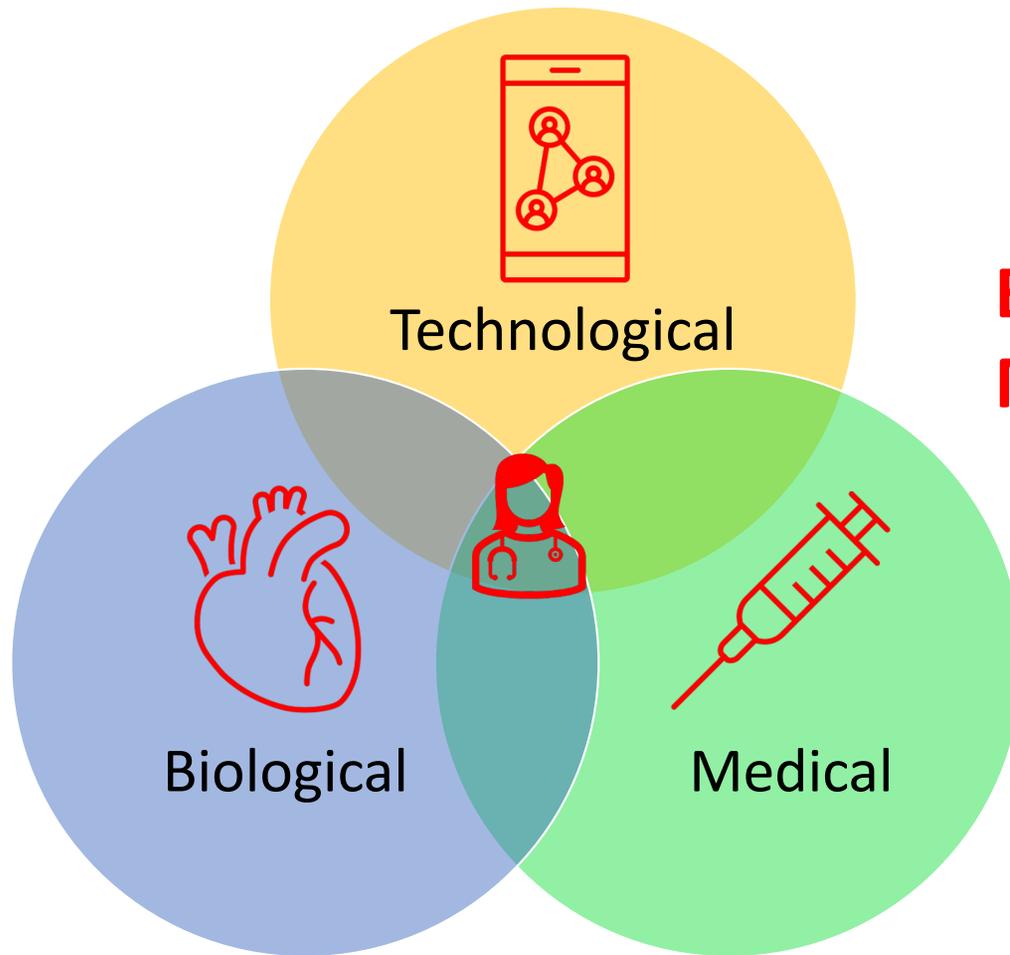
Main categories	Subcategories
Knowledge	<ul style="list-style-type: none"> <li>• Basic understanding of artificial intelligence</li> <li>• Statistics</li> <li>• Ethics</li> <li>• Data protection and regulation</li> </ul>
Interpretation	<ul style="list-style-type: none"> <li>• Critical reflection</li> <li>• Associated risks</li> <li>• Data basis</li> </ul>
Application	<ul style="list-style-type: none"> <li>• Practical skills</li> <li>• Trust</li> </ul>

McCoy LG, Nagaraj S, Morgado F, Harish V, Das S, Celi LA. What do medical students actually need to know about artificial intelligence? *NPJ Digital Medicine*. 2020;3:86.

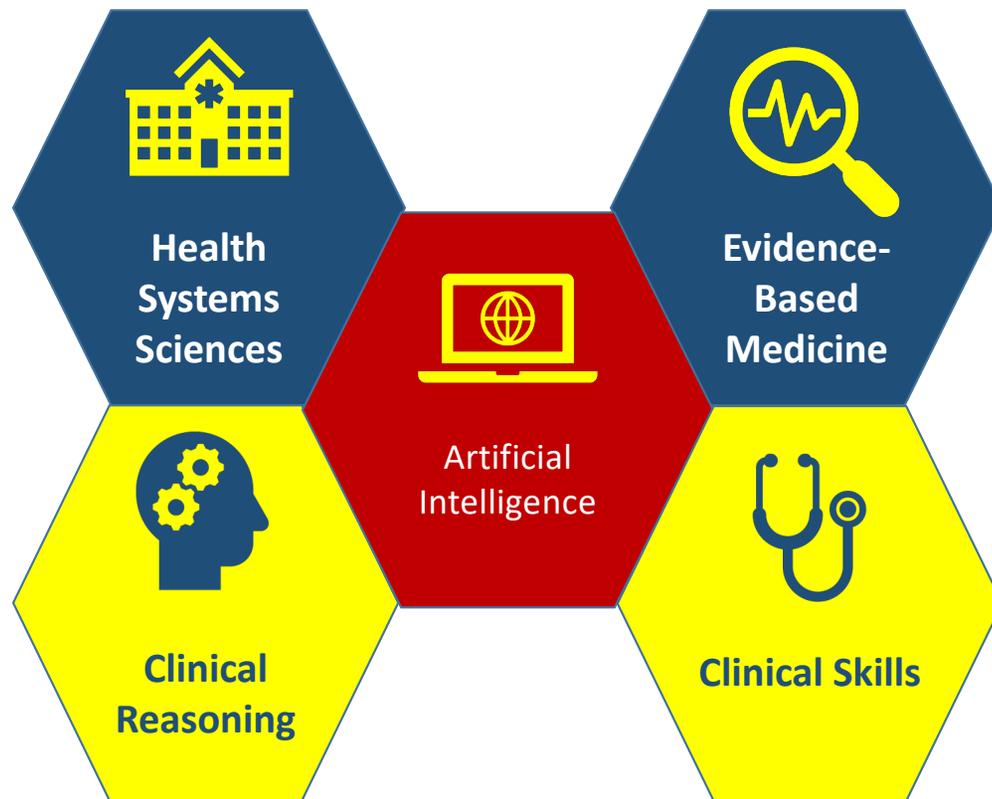


## Biomedical Model

Duffy TP. The Flexner Report--100 years later. *Yale J Biol Med.* 2011;84(3):269-276.



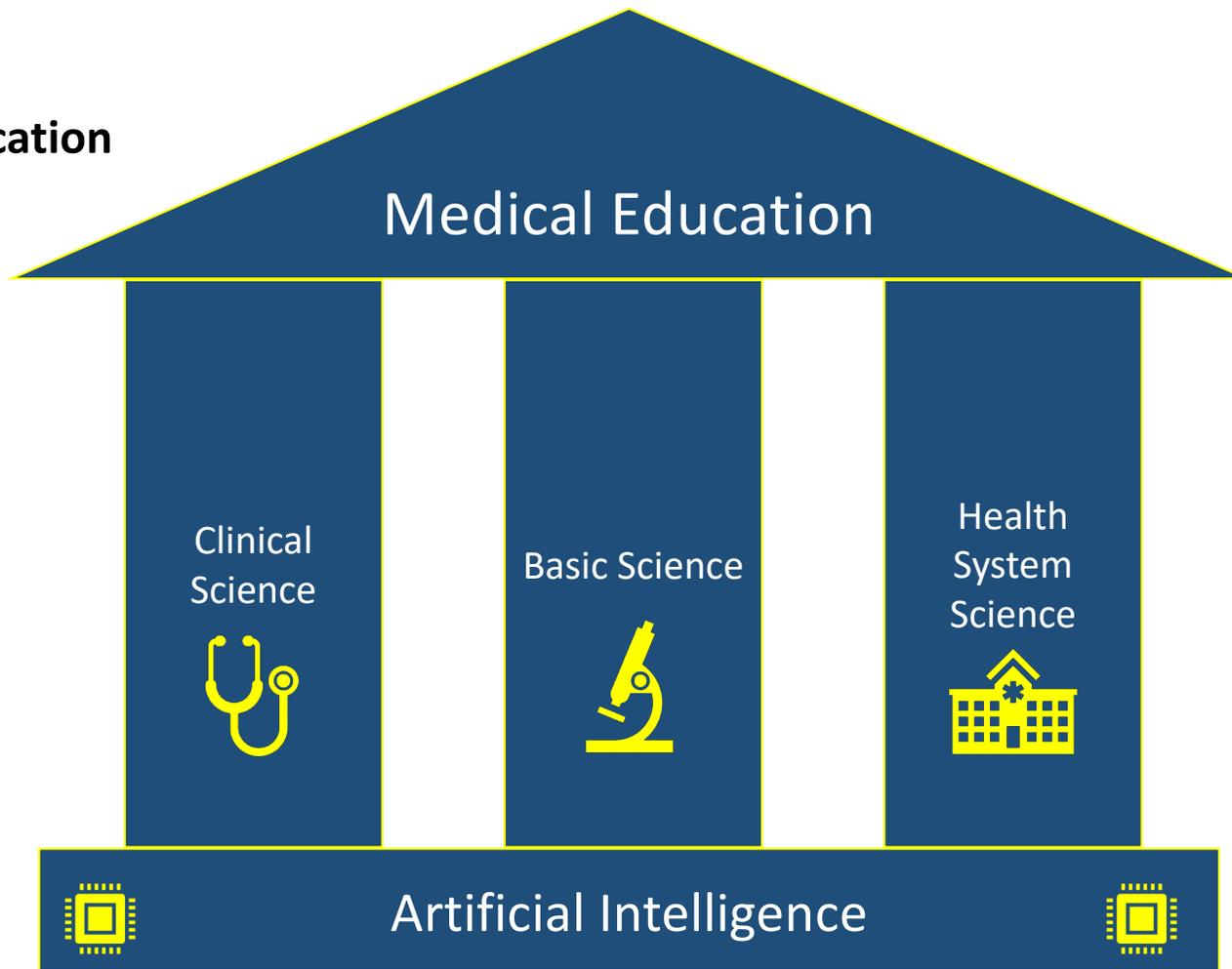
## **Biotechnomedical (BTM) Model**



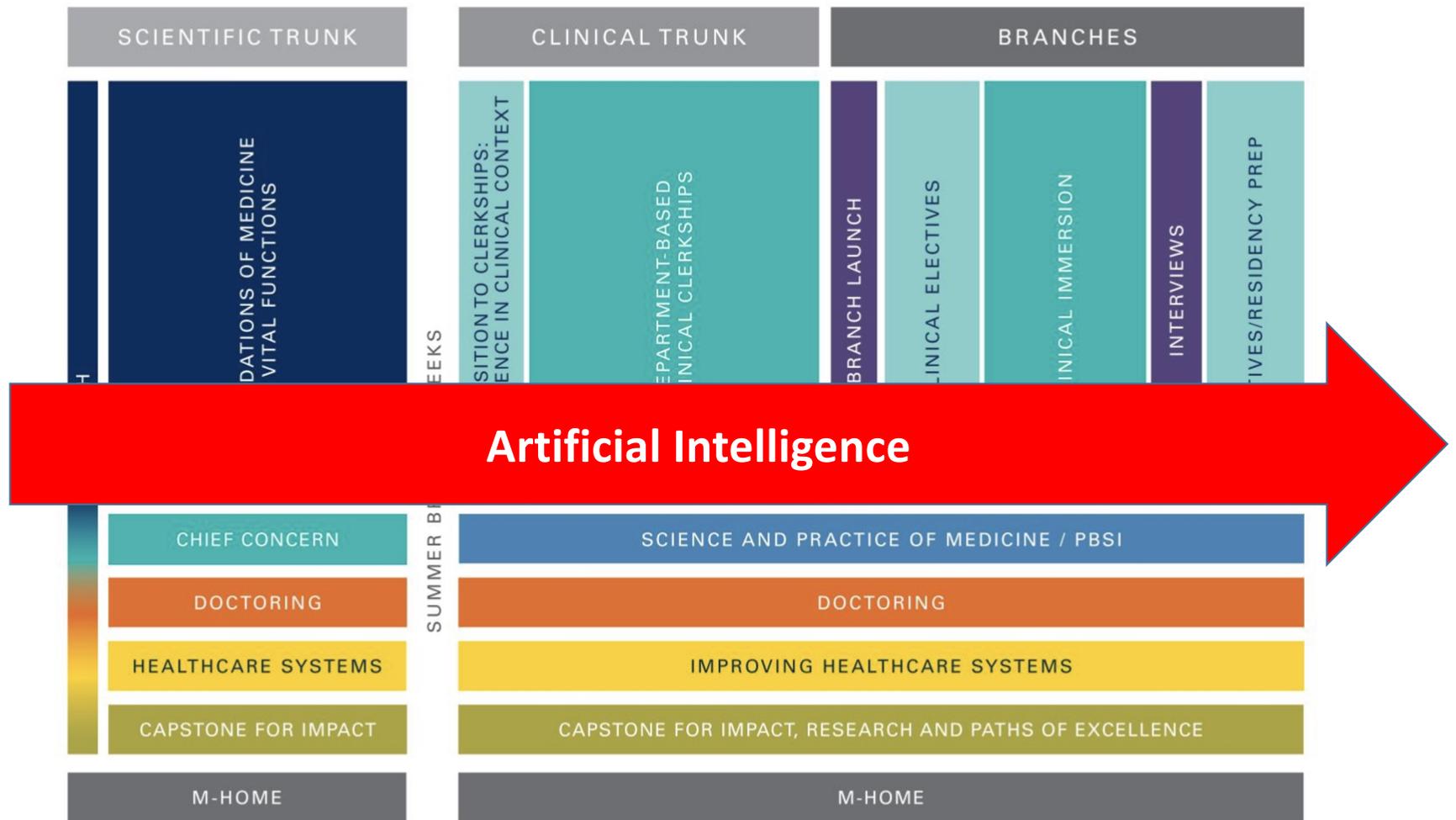
# Integration

James CA, Wheelock KM, Woolliscroft JO. Machine Learning: The Next Paradigm Shift in Medical Education. *Acad Med.* 2021;96(7):954-957.

## Pillars of Medical Education



Fred HL, Gonzalo JD. Reframing  
Medical Education. *Tex Heart Inst J.*  
2018;45(3):123-125.



# Biomedical Model

UMMS Scientific Trunk



Current State

# Biotechnomedical Model

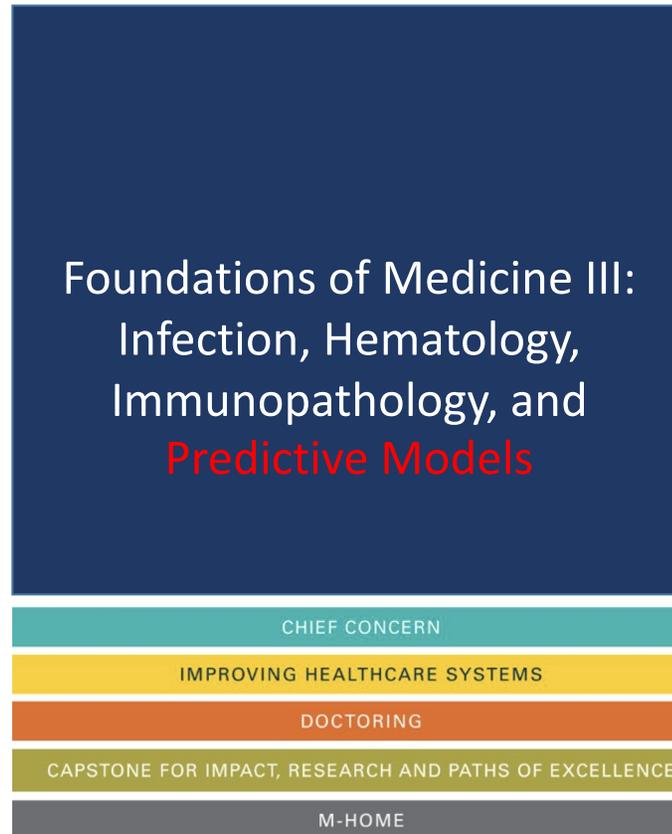
UMMS Scientific Trunk  
Block 1



Future State?

## Biotechnomedical Model Example

UMMS Scientific Trunk  
Block 6



Future State?

- **UMMS Block 6**
  - Hematology
  - Infectious diseases
    - Microbes, diagnoses, anti-microbials
    - Sepsis
- **EBM**
  - Critical evaluation of *Epic Sepsis Model* performance
- **Chief Concerns**
  - Integrating output of *Epic Sepsis Model* into clinical reasoning to generate a differential diagnosis
- **Doctoring**
  - Explaining the role of AI/ML (*Epic Sepsis Model*) in decision making
- **Health Systems Science (Improving Health Systems)**
  - Implementing the *Epic Sepsis Model* into the Health System
  - Workflow, regulation, etc.
- **Interprofessional Education**
  - Medical students, CSE students, law students, etc.
    - How could the model be improved?

Research

JAMA Internal Medicine | [Original Investigation](#)

## External Validation of a Widely Implemented Proprietary Sepsis Prediction Model in Hospitalized Patients

Andrew Wong, MD, Erkin Otles, MEng, John P. Donnelly, PhD, Andrew Krumm, PhD, Jeffrey McCullough, PhD, Olivia DeTroyer-Coolley, BSE, Justin Pestrue, MEcon, Marie Phillips, BA, Judy Konye, MSN, RN, Carleen Penzoza, MHSA, RN, Muhammad Ghous, MBBS, Karandeep Singh, MD, MMSc



UNIVERSITY OF MICHIGAN MEDICAL SCHOOL  
MICHIGAN MEDICINE

- **UMMS Block 6**

- Hematology
- Infectious diseases
  - Microbes, diagnoses, anti-microbials
  - Sepsis

Foundations of Medicine III:  
Infection, Hematology, Immunopathology, and  
**Predictive Models**

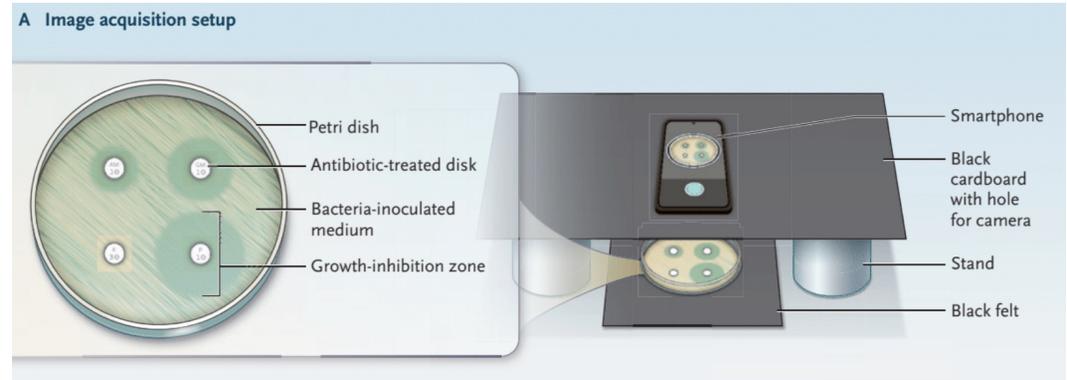
CHIEF CONCERN

IMPROVING HEALTHCARE SYSTEMS

DOCTORING

CAPSTONE FOR IMPACT, RESEARCH AND PATHS OF EXCELLENCE

M-HOME



**B Mobile application functionality**

**1 Machine learning-powered image processing**

Frame petri dish      Determine antibiotic type      Measure growth-inhibition zone

**2 "Expert System" driven by artificial intelligence for processing results**

Antibiotic Sensitivity Analysis	
Results	
Ampicillin 10 µg	S
Gentamicin 10 µg	R
Kanamycin 30 µg	/
Penicillin 10 µg	I
S Sensitive	
I Intermediate	
R Resistant	
/ Indeterminate	

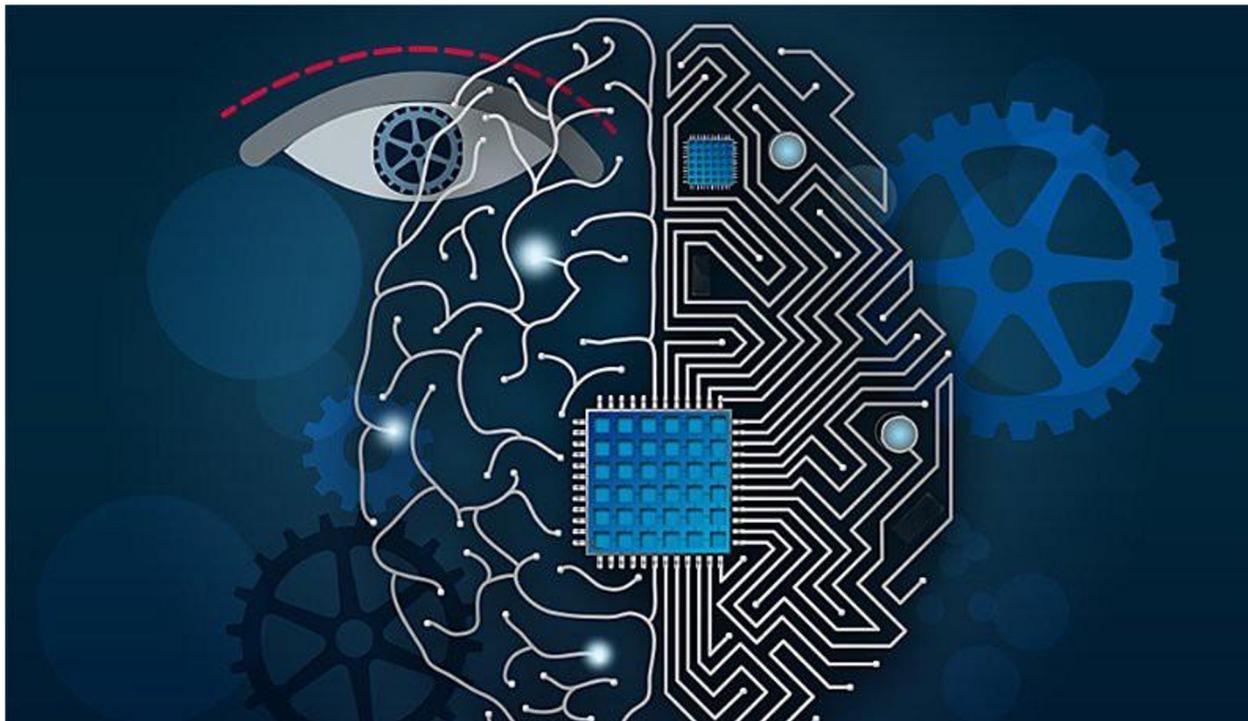
Create report

Antibiotic resistance levels are classified

Results can be sent to global surveillance systems

Brownstein JS, Rader B, Astley CM, Tian H. Advances in artificial intelligence for infectious disease surveillance. *NEJM*.

# Data Augmented, Technology Assisted Medical Decision Making (DATA-MD)



# DATA-MD Mission

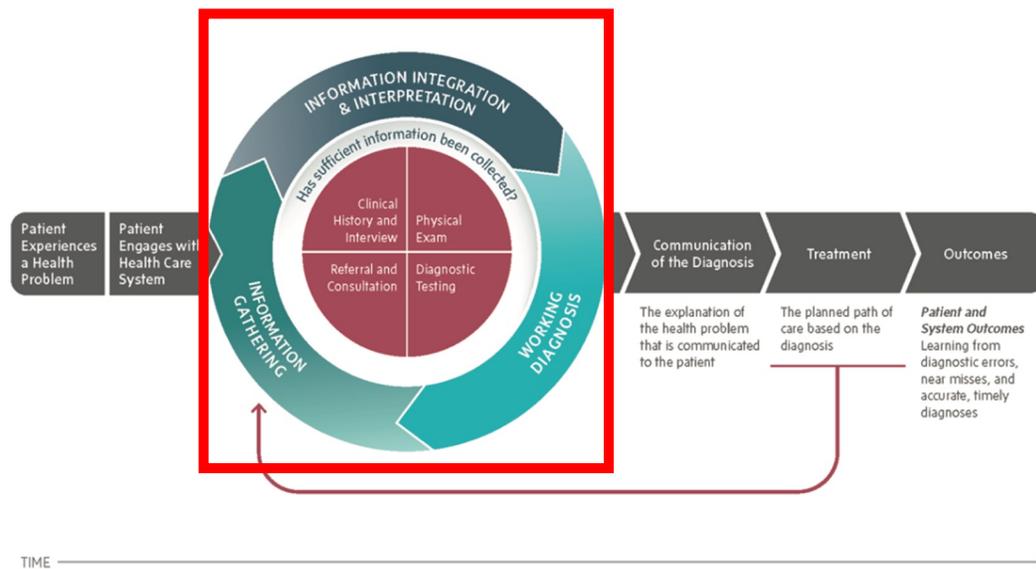
To develop, implement, and disseminate innovative health care AI/ML curricula that serve as a foundation for medical educators to develop curricula specific to their own institutions and/or specialties.

# DATA-MD Team

- Cornelius A. James, MD
- Nancy Allee, MLS, MPH
- Larry Gruppen, PhD
- Benjamin Li (medical student)
- Maggie Makar, PhD
- Brahmajee Nallamotheu, MD, MPH
- Nicholson Price, JD, PhD
- Karandeep Singh, MD, MSc
- Jessica Virzi, MSN
- Jenna Wiens, PhD
- James Woolliscroft, MD
- Andrew Wong, MD (U-M House Officer)



# DATA-MD and Frameworks



**NAM Diagnostic Process**



**UMMS Evidence-Based Medicine Process**

James CA, Wheelock KM, Woolliscroft JO. Machine learning: the next paradigm shift in medical education. *Acad Med.* 2021.96(7): 954-957.

# DATA-MD

- Use of AI/ML in diagnostic decision making
  - EBM framework
  - Bayesian approach
- Four online modules
  - Intro to AI/ML in Healthcare
  - Foundational Biostats and Epi in AI/ML for Health Professionals
  - Using AI/ML to Augment Diagnostic Decisions
  - Ethical and Legal use of AI/ML in the Diagnostic Process
- Launch 2023



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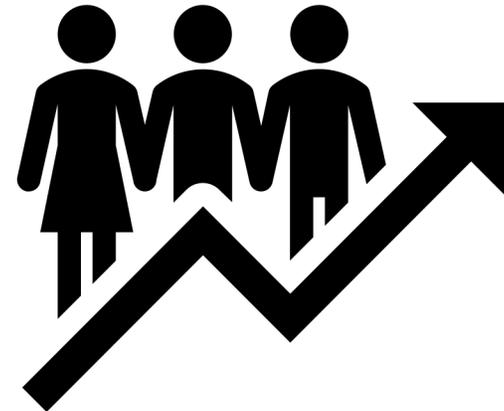
# DATA-MD

- Seven web-based modules
  - Intro to AI in Health Care
  - Methodologies
  - Diagnosis
  - Treatment and Prognosis
  - Law, Ethics, Regulation
  - AI in the Health System
  - Precision Medicine
  
- Launch 2023



# Next Steps

- Curricular review
  - School, course, session level
  - Re-prioritization
- Identify champion(s)
  - Learners, faculty, staff
  - Committees
- Interprofessional collaboration
  - Engage stakeholders
- Faculty development



# Take Home Points

- AI/ML in health care is here, and it will continue to march forward with or without physicians.
- AI/ML has the potential to transform the way medicine is practiced.
- Currently, AI/ML instruction in medical education is lacking.
  - We must begin to consider how we incorporate this content into curricula.
- Interprofessional collaboration is essential.